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# Analyzing Critical Success Factors for Sustainable Cloud-Based Mobile Learning (CBML) in Crisp and Fuzzy Environment

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**Abstract:** Mobile Learning (M-Learning), driven by technological digital advancement, is one of the essential formats of online learning, providing flexibility to learners. Cloud-based mobile learning (CBML) provides value additions by providing an economic alternative to E-learning. Revolutionary changes in smartphone design and features have enhanced the user experience, thus encouraging mobile learning. During the COVID-19 pandemic, E-Learning and M-Learning allowed continuing education to occur. These methods continue to offer more opportunities to learners than constrained face-to-face classroom learning. There are many main critical success factors (CSFs) and subfactors that play an influential role in sustainable M-Learning success. The current study focuses on the assessment and ranking of various main factors and subfactors of CBML. Analytic hierarchy process-group decision-making (AHP-GDM)- and fuzzy analytic hierarchy process (FAHP)-based methodologies were used to evaluate and model the main factors and subfactors of CBML in crisp and fuzzy environments. Higher education institutes must strive to address these main factors and subfactors if they are to fulfill their vision and mission in the teaching–learning system while adopting sustainable M-Learning.

**Keywords:** analytic hierarchy process (AHP); cloud-based M-Learning (CBML) cloud computing; fuzzy AHP (FAHP); mobile learning; universities; higher educational institute



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## 1. Introduction

Changing technology helps students gain instant access to knowledge and rapid learning methods, while also providing fun opportunities to put what they have learned into practice. Additionally, technology enables students to learn about new topics and gain a better understanding of complex topics [1]. Mobile learning (M-Learning) is an increasing trend in education institutions, thanks to advances in mobile technology that have enabled schooling, training, and learning on the go. In today's dynamic environment, universities and colleges that want to compete must keep coming up with new ways to outperform their peers. It would not be sufficient to focus solely on the efficiency of educational facilities. Institutions have thus been attempting to maximize their effects on students to gain a strategic competitive advantage over rivals and peers. M-Learning, as a novel technology, can have a significant impact, especially for huge universities [2]. Mobile technology has improved the efficacy of online learning and made it possible to use technology to help the learning process at universities and college campuses. Although the use of mobile devices is growing, many researchers and practitioners have integrated mobile learning into education systems. M-Learning is a cutting-edge method of mobile device-assisted teaching and learning that uses user-friendly software platforms, text and video-based learning, and instructor-led or virtual instructor-based learning [3]. M-Learning allows students to engage in customized, blended learning on their smartphones. In recent years, we've seen a slew of new mobile services integrate sustainable mobile technology into university teaching practices, resulting in higher course completion rates and graduation rates for university students [4,5].

Mobile phones have become an important part of many people's daily lives around the globe. According to Statista, the number of individuals using cell phones has surpassed 6.5 billion, and this figure is expected to rise rapidly. Figure 1 shows projected global mobile phone users from 2020 to 2024 [6]. M-Learning is rapidly gaining traction, particularly in the post-COVID period. Many recent studies have provided insights into the growing M-Learning industry.

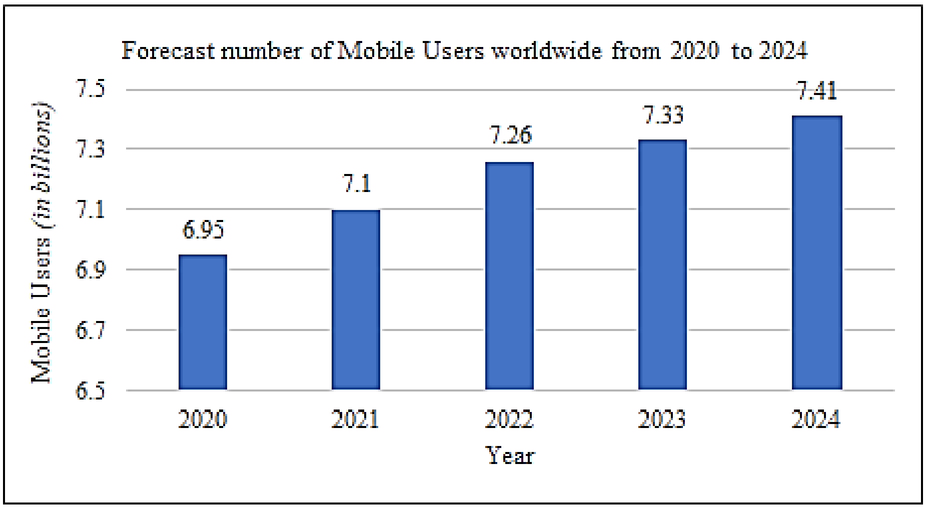


**Figure 1.** Worldwide projected mobile phone users, 2020–2024 [6].

Cloud computing has expanded rapidly and has had a major impact on human lifestyles as a result of information technology (IT). To survive the present economic depression, many firms have turned to cloud computing. Without requiring significant resources to be allocated to a physical data center, cloud computing can provide a range of IT services, including data center services. These services can be obtained at a reduced overall cost, in comparison to physical resources, giving users a competitive advantage and reduced operating expenses [7]. Cloud-based ICT infrastructure contributes to sustainability by facilitating on-demand flexible expansion, cost savings, and new solutions [8]. Cloud computing is described as "a model for allowing appropriate access to IT resources such as (e.g., servers, storage, services, networks resources, and software) which could begin functioning with minimal intervention from the service supplier and administration". Cloud mobile computing is an environment that enables various kinds of mobile devices to access computer resources from anywhere, at any time. The combination of cloud computing and a mobile environment is known as cloud mobile computing. It describes a system in which data are processed and stored away from mobile devices [9]. The cloud-based M-Learning (CBML) system became indispensable during the COVID-19 pandemic. Hence, in order to maximize its beneficial potential, it needed be studied further.

The present study aimed:

- to identify the importance CSFs CBML system by analyzing the literature;
- to prepare a model for the evaluation and prioritization of sustainable CBML CSFs using the analytic hierarchy process group decision-making (AHP-GDM) and fuzzy AHP (FAHP).

The paper is organized as follows: Section 2 shows the CSFs identification framework for CBML, Section 3 provides a detailed description of the AHP-GDM and FAHP methodologies, while Section 4 provides a case illustration and application. Section 5 shows the results and discussions on the evaluation ranking of CSFs of CBML. Section 6 provides the discussion and limitations on the CSFs of CBML, followed by our conclusions.

## 2. Related Works

Several studies were found on CBML system selection in the literature. This section was categorized as the multi-criteria decision-making (MCDM) and CSFs identification framework for CBML.

### *2.1. MCDM Methodologies*

An in-depth review of the literature was carried out on success factors in CBML, and an MCDM model was developed. Different researchers have used MCDM in a variety of applications; it has been used for sorting, ranking, and identifying the best potential factors of a given set. One popular MCDM technique, employed for prioritizing and ranking various elements, is AHP [10].

Adem [11] conducted a study to analyze and assess online education platforms based on human-computer interaction factors. Using MCDM methodologies, they determined the best and most appropriate distant learning platform for classroom instructions for both teachers and learners.

Celikbilek [12] used fuzzy DEMATEL and ANP to investigate the relationships between the various factors of E-Learning systems and subsequent ranking for the stakeholders. This helped users understand the causal relations between the different E-Learning components. The study analyzed 19 E-Learning system components, which were organized into three main domains: E-Learning, Education, and Technology. Tang [13] employed MCDM and evaluated interactions among the critical factors related to marketing-oriented strategic alliances during different stages in the telecommunications industry. The study showed different relationships and determined whether sustainable collaboration in different stages was possible. They used different usability factors to find and rank academic websites. Fuzzy AHP was found to be a useful method and was used to set up a framework for usability evaluation [14]. Various aspects of academic integrity were analyzed while using E-Learning in Saudi Arabian universities. They discovered 12 attributes, associated with the E-Learning environment and academic integrity awareness, using a comprehensive literature analysis and the Delphi technique. These factors were then prioritized using the AHP technique [15].

Murat [16] developed an intelligent software program for evaluating and selecting questions. Named the "Intelligent question evaluation and selection software (I-QUESS)", the proposed hybrid system was utilized to develop a digital test sheet that allowed users to select questions based on their preferences using a hybrid of FAHP and genetic algorithms (GA) [16]. Quadri [17] identified different success factors and their dimensions for cloud-based E-Learning. Furthermore, they employed MCDM to evaluate and rank each factor to find the influence of each factor on others.

### *2.2. Framework for The Identification of Factors in CBML*

The factors that must be measured in each stage of planning, development, and operation are known as CSFs [17]. They can assist in discovering, regulating, and monitoring the success of a high-quality cloud-based M-Learning system. CSFs play a significant role in CBLL as they directly or indirectly influence the success of CBLM. While carrying out the literature review, it is observed that several studies determined lead identification of CSFs of CBML. Based on such studies, various CSFs, suggested by several researchers, were critically examined—as it is difficult to model CSFs to identify their importance in the success of CBLM. To ensure all the significant CSFs were covered in the present study, the systematic framework leading to the whole process was derived. Figure 2 shows the CSF selection framework for CBML. Using the expert knowledge of decision-makers (DMs), 21 CSFs were shortlisted. DMs were quite careful while choosing CSFs from the identified

CSFs of 25. For several reasons (for instance, redundancy, not applicable to CBML, etc.), four CSFs were dropped. Thus, DMs ensured the influence of the selected CSFs of CBML that were potentially responsible for CBML's involvement in the teaching–learning system. As per the feedback from DMs, 17 CSFs were shortlisted and grouped into four main CSFs, i.e., Cloud Services Compliance (CSC), Cloud M-Learning Essentials (CLE), System and Technological Advancement (STA), and Organizations' Management Readiness (OMR). Later on, AHP-GDM and FAHP-based modeling were carried out following the framework. The various main factors and subfactors of CBML chosen are discussed below:

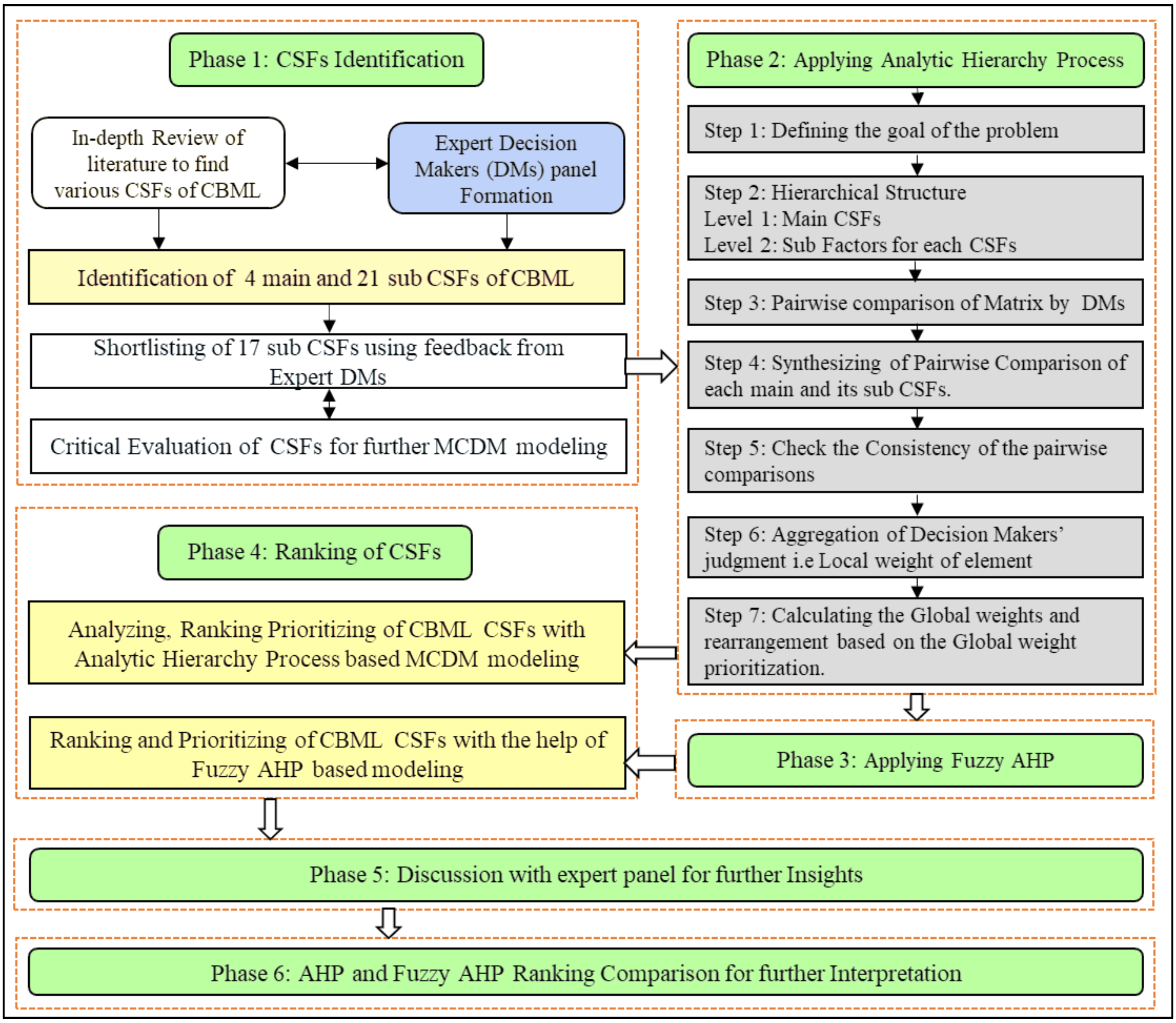


**Figure 2.** The framework for shortlisting CSFs for CBML.

### 2.3. CSFs of CBML

Although cloud-based learning systems are still in their infancy, it has been shown that they are beneficial when used in higher education. However, learning via mobile devices is constrained in terms of processing and computation capacity, memory space, and infrastructure for some software applications [18]. There are many significant advantages to using cloud computing and mobile technology together. It is important to note that IT has aided in users' extensive adoption and utilization of ICT in education. For the present study, literature was reviewed in the areas of E-Learning, mobile learning, and CBML uptake in institutions from various research databases, including Web of Science, Scopus, and Google Scholar. The literature review was targeted with various keywords, e.g., critical success factors, main factors, and enablers of mobile learning or cloud mobile learning or CBML from 2014 to the present. Finally, CSFs related to CBML were compiled and categorized into four domains, as discussed below.

### *2.4. Cloud Services Compliance Factor*

The term cloud services describe several environments and services made available to businesses and consumers over the internet upon request. These services are designed to provide easy, affordable access to apps and virtual infrastructure without the need for internal hardware or infrastructure [18]. Other subfactors associated with this factor include a cloud service-level agreement which acts as a contract that ensures a specific quality of service between organizations that provide cloud services and educational institutions [8,19]. Cloud computing's use of data privacy makes it possible to gather, store, transmit, and disseminate knowledge without endangering the privacy of individual users' data [9]. There have been some challenges associated with security and privacy during the execution of cloud-based M-Learning [20] in universities. These need to be addressed of by providers and users of cloud services in order to ensure that the whole system is reliable and always available for students, instructors, and other users [21].

### *2.5. Cloud M-Learning Essentials Factor*

This factor focuses on the elements required to complete the ecological cycle of successful cloud-based mobile learning. A supportive and collaborative environment is the primary reason to move on [18,22]. Similarly, user's digital literacy and attitude [4] help in the system's perceived utility becoming successful. There is also the subjective perception of those who think that utilizing particular technology will increase their productivity, and the desire to use CBML as a crucial component in finishing difficult assignments [23–25]. Last but not least, there needs to be some acceptance that the degree to which a new product outperforms an older one is a perceivable relative benefit of CBML [9].

### *2.6. System and Technological Advancement*

To take advantage of all of the benefits of CBML, institutions must have adequate systems and technological infrastructure [26]. Good configuration of cloud learning devices [24] with institutions' compatible mobile learning applications is crucial and can be used as a starting point for educational materials. User-friendly design [22] and good quality internet bandwidth [20,21] are necessary for the successful implementation of CBML. Of course, the speed and quality of broadband connections are affected by several things. These could include the transfer technique, user locality, the number of individuals with whom users share the link, and the device used. There are additional distinctions between mobile and fixed networks.

### *2.7. Organizations' Management Readiness*

Top management support is critical for any significant IT deployment, and this is equally true for CBML. The link between employees, procedures, technologies, and performance measurement is referred to as organizational preparedness and readiness. There can be no effective execution without collaboration among all the stakeholders of the organization. Service support [24], Increased Productivity [27], and Organizational Culture and Commitment toward M-Learning [28] are the important subfactors of this dimension. Table 1 provides the list of factors and subfactors, along with their references.

**Table 1.** CSFS and subfactors related to CBML.

| Factors | Subfactors | References |
|---|---|---|
| Cloud Services Compliance (CSC) | Cloud Services (SaaS, PaaS, IaaS) (CS) | [8,9,29–34] |
| | Service Level Agreement (SLA) | [8,19] |
| | Data Security and Privacy (DSP) | [8,9,18–21,26,27,33,35–37] |
| | Reliability and Availability (RAA) | [8,19,21,34,37] |
| Cloud M-Learning Essentials (CLE) | Collaborative M-Learning Environment (CLE) | [1,2,5,18,22,35,38–43] |
| | User's Digital Literacy & Attitude (UDA) | [1,4,19,22–24,38,42,44–48] |
| | Perceived Usefulness (PU) | [2,4,8,9,18,23–25,34,36,39,49–51] |
| | Motivation (MO) | [1,24,38,39,43,48,49] |
| | Relative advantage (RA) | [8,9,24] |
| System and Technological advancement (STA) | Cloud Learning Devices (CLD) | [18,21,30,35,38,42,46,47] |
| | Technological Compatibility (TC) | [1,8,19,21–24,28,32,36,38,41,44,46,47] |
| | User-Friendly Design (UFD) | [8,9,22,34] |
| | Internet Bandwidth (IB) | [5,8,18–22,26,27,40,52,53] |
| Organizations Management Readiness (OMR) | Service Support (SS) | [1,8,19,24,34,36,38,40,47] |
| | Increased Productivity (IP) | [21,22,25,27,36,37,39] |
| | Organizational Culture (OC) | [2,5,19,28,37,54] |
| | Commitment toward M-Learning (CTL) | [25,39,40,47,54,55] |

## 3. Overview of the AHP and FAHP

The present section provides the research methodologies based on MCDM. The AHP-GDM is employed as systematic group decision-making to remove DM's bias while solving complex problems consisting of multiple conflicting criteria. FAHP is preferred over AHP as it enables higher accuracy during decision-making by removing vagueness that persists in decision-making. In this study, we used FAHP, along with basic fuzzy set theory and extension principles.

### *3.1. AHP Methodology*

AHP is a systematic decision-support method put forward by T.L. Saaty and used by many researchers in problem-solving involving simple to complex hierarchies. The AHP procedure may resolve simple or complex problems consisting of conflicting criteria with different levels of hierarchy and structural complexity. The application of AHP may be found in various types of research and in various applications [15,17,56–59].

The DMs judgment is derived through a pairwise ca scale, as shown in Table 2. DMs play a significant role in pairwise comparison. The pairwise comparison calls for expertise from DMs; however, bias can occur if a single DM is involved in decision-making, rendering a decision misleading and/or unusable. The most robust decision-making and accuracy may be accomplished by increasing the number of decision-makers in the panel DM. The GDM process may employ more DMs to resolve the given problem based on their availability.

**Table 2.** AHP scale [58].

| The Intensity of Relative Importance | Definition |
|---|---|
| 1 | Equally preferred |
| 3 | Moderately preferred |
| 5 | Essentially preferred |
| 7 | Very strongly preferred |
| 9 | Extremely preferred |
| 2, 4, 6, 8 | Intermediate importance between two adjacent judgements |

The detailed AHP-GDM process is further explained below:

Step 1. The various shortlisted CSFs of CBML are structured to form a single hierarchy. Later on, these are converted to form a comparison matrix or a decision matrix '*D*'. A pairwise matrix may be formulated as '*D*' matrix. The element, $d_{mn}$ of the '*D*' matrix, may be compared with the *m*th element with that of the *n*th in terms of its importance level.

$$D = \begin{bmatrix} d_{11} & d_{12} & \dots & d_{1n} \\ d_{21} & d_{22} & \dots & d_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ d_{m1} & d_{m2} & \dots & d_{mn} \end{bmatrix} \quad (1)$$

Step 2. The '*D*' is formulated based on the participation of DMs. Further geometric means may be calculated for each pairwise decision matrix. On conversion of the matrix using GM, a priority vector (*PV*) may be derived.
Step 3. In the decision matrix '*D*', all the entries are according to their pairwise formulations values. Thus, an overall summation of the sum-product of each vector column for both the matrices with the *PV* values of each row is calculated. Later on, the principal eigenvalue ($\lambda_{max}$) may be calculated using Equation (2).

$$\lambda_{max} = \sum_{i,j=1}^{k} C_j PV_i \quad (2)$$

Here, $c_j$ represents the summation of each column vector.

Step 4. In AHP, the consistency index (*CI*) of decision-making is crucial for its acceptance in further calculation. An inconsistent decision is rejected and DM is asked to provide a new pairwise decision. Thus, the accuracy is maintained in AHP by keeping watch on the consistency of decision-making, obtained by Equation (3).

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (3)$$

Here, *n* is the matrix order.

Step 5. The random index (*RI*) may be calculated using Equation (4). The *RI* may be directly obtained from Table 3 based on the matrix size.

$$RI = \frac{1.98\ (n-2)}{n} \quad (4)$$

**Table 3.** RI table.

| ***n*** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** | **9** | **10** |
|---|---|---|---|---|---|---|---|---|---|---|
| *RI* | 0.00 | 0.00 | 0.58 | 0.90 | 1.12 | 1.24 | 1.32 | 1.41 | 1.45 | 1.49 |

Step 6. The critical value of CR is less than 10%. Hence, any pairwise matrix not meeting this significance value may be rejected and revised again. The value is calculated from the ratio of *CI* and *RI*.
Step 7. The various pairwise matrix may be combined into a single matrix using geometric mean to obtain a single decision.

### *3.2. FAHP Methodology*

The use of fuzzy numbers can provide more accurate decision-making in FAHP as compared to AHP. The fuzzy set theory, along with various rules, may render itself useful by employing triangular fuzzy numbers (TFNs). A typical TFN depicted in Figure 2 may be used in deriving the pairwise comparison. The extension principle can be useful while finding the intersections of such TFNs. The use of TFN also helps in reducing biases [60]. The fuzzy set theory, along with extension principles, is briefed in Figure 3.

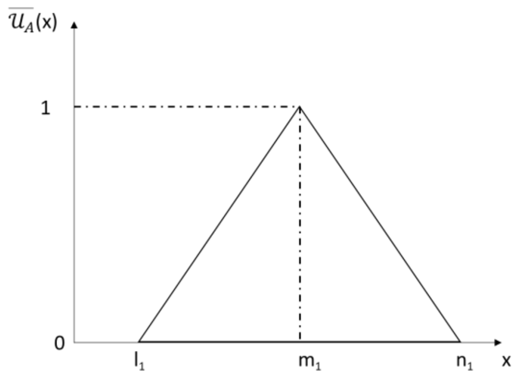


**Figure 3.** Triangular fuzzy number (P).

#### 3.2.1. Basic Fuzzy Set Theory

The fuzzy set theory provides good and efficient decision-making. Fuzzy set theory-based rules also provide flexibility to DM. Thus, in a fuzzy environment, using fuzzy set theory and the fuzzy extension principle can help make good decisions.

The triangular fuzzy numbers (TFN) (a_1, a_2, a_3) or trapezoidal numbers (TrFN) (a_1, a_2, a_3, a_4) can be used in pairwise decision-making [61–63] as shown in Figure 3.

The fuzzy set theory uses TFNs for various arithmetic operations [60]. TFNs may be represented by $D_1$ and $D_2$ as ($k_1$, $m_1$, $n_1$) and ($k_2$, $m_2$, $n_2$), respectively.

Two TFNs can be used to perform arithmetic operations such as subtraction, addition, division, and multiplication. Such arithmetic operations can be represented by the following Equations (5)–(9):

$$\widetilde{D}_1 \oplus \widetilde{D}_2 = (k_1 + k_2,\ m_1 + m_2,\ n_1 + n_2) \tag{5}$$

$$\widetilde{D}_1 \ominus \widetilde{D}_2 = (k_1 - k_2,\ m_1 - m_2,\ \ n_1 - n_2) \tag{6}$$

$$\widetilde{D}_1 \otimes \widetilde{D}_2 = (k_1 k_2,\ m_1 m_2,\ \ n_1 n_2) \tag{7}$$

$$\lambda \otimes \widetilde{D}_1 = (\lambda_1 k_1, \lambda_1 m_1,\ \lambda_1 n_1)\ where\ \lambda > 0,\ \lambda \epsilon\ R \tag{8}$$

$$\widetilde{D}_1^{-1} = \left(\frac{1}{n_1}, \frac{1}{m_1}, \frac{1}{k_1}\right) \tag{9}$$

#### 3.2.2. Extent Analysis in MCDM in Fuzzy Environments

Using the extent principle, two triangular fuzzy numbers (TFNs) can be compared [17]. Two sets may be considered as a set of priorities and a set of targets, i.e., $Y = \{y_1, y_2, \ldots\ldots\ldots, y_n\}$ and $Z = \{z_1, z_2, \ldots\ldots\ldots, z_n\}$, respectively. Furthermore, this objective is accomplished using the extent principle to achieve each objective. As a consequence, the values obtained are:

$$Q_{gi}^1, Q_{gi}^2 \ldots Q_{gi}^m,\ i = 1, 2, \ldots, n \tag{10}$$

Here, $Q_{gi}^j$ $(j = 1, 2, \ldots m)$ are TFNs and represented as $(p,\ q,\ r)$. The method is explained below, based on the extent analysis as described by [61].

Step 1: Preparation of hierarchical structure for the objective.

The CBML framework is divided into many categories, including main factors and subfactors. Framing the hierarchical system for ranking in the MCDM problem is an important task. The hierarchy is prepared in consultation with DMs.

Step 2: Carrying out the pairwise comparison for dimension and CSFs of M-Learning using TFNs.

The main factors and subfactors of CBML can be evaluated using the DMs' feedback. The pairwise comparison of the main factors and subfactors of CBML is accomplished using TFN.

Step 3: Calculating the value of fuzzy synthetic extent.

$$F_i = \sum_{j=1}^{m} Q_{gi}^{j} \otimes \left[\sum_{i=1}^{n}\sum_{j=1}^{m} Q_{gi}^{j}\right]^{-1} \tag{11}$$

Using fuzzy summation of TFNs, $m$ extent analysis values $\sum_{j=1}^{m} Q_{gi}^{j}$, may be obtained as:

$$\sum_{j=1}^{m} Q_{gi}^{j} = \left(\sum_{j=1}^{m} p_j, \sum_{j=1}^{m} q_j, \sum_{j=1}^{m} r_j\right) \tag{12}$$

and $\left[\sum_{j=1}^{n}\sum_{j=1}^{m} Q_{gi}^{j}\right]^{-1}$, gives the fuzzy summation of $Q_{gi}^{j}(j = 1, 2, \ldots, m)$ values are calculated as:

$$\sum_{i=1}^{n}\sum_{j=1}^{m} N_{gi}^{j} = \left(\sum_{j=1}^{m} p_j, \sum_{j=1}^{m} q_j, \sum_{j=1}^{m} r_j\right) \tag{13}$$

The inverse of the vector may be obtained as:

$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m} Q_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} r_i}, \frac{1}{\sum_{i=1}^{n} q_i}, \frac{1}{\sum_{i=1}^{n} p_i}\right) \tag{14}$$

Step 4: Obtaining the degree of possibility of supremacy for two TFNs i.e., $Q_2 = (p_2, q_2, r_2) \geq Q_1 = (p_1, q_1, r_1)$

$$V(Q_2 \geq Q_1) = sup\left[min(\mu_{Q_1}(x), \mu_{Q_2}(y))\right], \; y \geq x \tag{15}$$

The equation can be represented as:

$$V(Q_2 \geq Q_1) = hgt\;(Q_1 \cap Q_2) = \mu_{Q_2}(f) \tag{16}$$

$$\mu_{Q_2}(f) = \begin{cases} 0 & if\; q_2 \geq q_1 \\ 1 & if\; p_1 \geq r_2 \\ \frac{p_1 - p_2}{(q_2 - p_2) - (q_1 - p_1)} & otherwise \end{cases} \tag{17}$$

The GDM may involve several DMs; for example, $K$ DMs may be participating, thus the subsequent pairwise comparisons yield $n$ elements. A set of $K$ matrices, $\breve{A}_k = \left\{\breve{q}_{ijk}\right\}$, where $\breve{A}_k = \breve{q}_{ijk} = \left(p_{ijk}, q_{ijk}, r_{ijk}\right)$ represents an element's relative importance $i$ to $j$, as derived by DM $k$. Later, Equation (19) could be used to perform the aggregation.

$$\left.\begin{array}{c} p_{ij} = min\left(p_{ijk}\right), \; k = 1, 2, \ldots k \\ q_{ij} = \sqrt[k]{\prod_{k=1}^{K} q_{ijk}} \\ r_{ij} = max\left(r_{ijk}\right), \; k = 1, 2, \ldots k \end{array}\right\} \tag{18}$$

The intersection of two TFNs, i.e., $(p_1, q_1, r_1)$ and $(p_2, q_2, r_2)$, is shown in Figure 4. The intersection is shown as ordinate $d$, representing the highest possible fuzzy numbers intersection $Q_1$ and $Q_2$ . Furthermore, $Q_1$ and $Q_2$, may be determined using the values of $V$ $(Q_1 \geq Q_2)$ and $V$ $(Q_2 \geq Q_1)$.

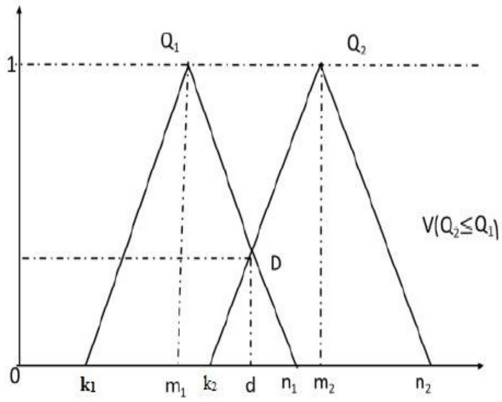


**Figure 4.** The intersection of TFNs [15].

Step 5: Establish the degree of possibility of convex fuzzy number so that it is greater than k convex Fuzzy number $Q_1(i = 1, 2, \ldots, k)$ may be derived as:

$$\begin{aligned} V\ (Q \geq\ Q_1, Q_2 \ldots Q_k) = V[(Q \geq Q_1)\ and\ (Q \geq Q_2\ and \ldots \ldots \ldots and\ (Q \geq Q_k))] \\ = minV\ (Q \geq Q_i),\ i = 1, 2, \ldots \ldots \ldots,\ k \end{aligned} \tag{19}$$

Considering,

$$d'(B_i) = minV(S_i \geq S_k)\ for\ k = 1, 2, \ldots \ldots, m; k \neq i \tag{20}$$

The weight vector may be obtained as $G' = (d'(B_1), d'(B_2), \ldots \ldots \ldots, d'(B_n))^T$
Such that $B_i(i = 1, 2, \ldots \ldots, n)$ has $n$ elements

Step 6: Calculate the normalized weight vectors.

The normalized weight vector may be obtained using Equation (23)

$$C = (d(B_1), d(B_2), \ldots \ldots \ldots,\ d(B_n))^T \tag{21}$$

where $C$ denotes a crisp number after defuzzification.

Step 7: Obtaining the total score of each dimension of CSFs and its prioritization factors.

The local weight and global weight products will represent the total priority weights of each main factor and subfactor of CBML. To achieve higher-order priorities, the main factors and subfactors of CBML may be ranked as per the required order.

## 4. Application of AHP-GDM and FAHP in CBML

MCDM methodologies like AHP and FAHP are preferred because of their simple and effective decision-making while carrying out the prioritization and ranking of criteria under a simple and complex hierarchy. AHP-GDM may be useful in synthesizing the opinion of several DMs, whereas FAHP further removes biases from decision-making. Generally, DMs play a vital role in qualitative analysis. In the present study, a team of three DMs with commendable experience in CBML was approached to help in the decision-making for an educational cause, to which they agreed readily. The team also included two reviewers to review the pairwise judgment and help in the overall assessment. The team of DMs and reviewers gave their unconditional consent for the use of data for further analysis. The profiles of the DMs and reviewers are shown in Table 4.

**Table 4.** DM and reviewer profiles.

| Sr. | Participants' Role | Job Designation | Degree | Experience in Years (Mobile and E-Learning) |
|---|---|---|---|---|
| 1 | Decision Maker 1 | Professor | PhD | 15 |
| 2 | Decision Maker 2 | Associate Professor | PhD | 10 |
| 3 | Decision Maker 3 | Associate Professor | PhD | 9 |
| 4 | Reviewer | E-Learning unit Head | PhD | 12 |
| 5 | Reviewer | E-Learning Instructor | PhD | 10 |

For the identification of CBML factors, a systematic framework was followed as discussed earlier. The in-depth analysis of the literature was considered to identify 4 main and 17 subfactors of CBML, as shown in Figure 5.

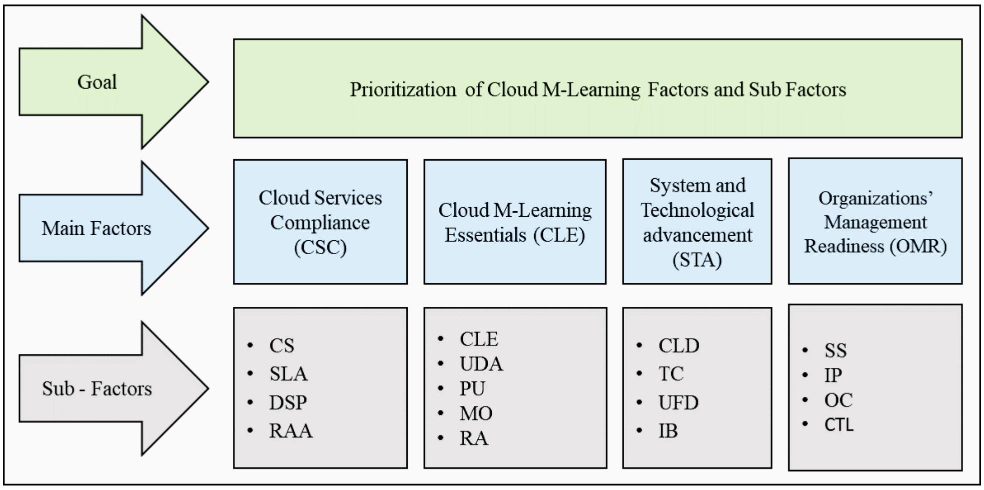


**Figure 5.** Hierarchy of main factors and subfactors of CBML.

The help of DMs was sought during the shortlisting of the main factors and subfactors of CBML. As per the AHP-GDM and FAHP steps discussed in the previous section, they were carried out to obtain various matrixes, tabulated in Tables 5–7. Table 8 shows the weight of the value after synthesizing all the values of the three decision matrices using the geometric mean. Local weights were obtained to provide the priority of subcriteria, whereas global weights provided the overall priority of main CSFs of CBML. Furthermore, a pairwise comparison of different main factors and subfactors was also carried out. The composite weight of all main factors and subfactors of CBML was obtained through the AHP-GDM, as shown in Table 9.

**Table 5.** Comparison of main CSFs Of CBML by DM1.

| Main CSFs of CBML | OMR | CLE | CSC | STA | Eigenvalue |
|---|---|---|---|---|---|
| Organizations' Management Readiness (OMR) | 1 | 2 | 3 | 2 | 0.4155 |
| Cloud M-Learning Essentials (CLE) | 1/2 | 1 | 2 | 3 | 0.2895 |
| Cloud Services Compliance (CSC) | 1/3 | 1/2 | 1 | 2 | 0.1693 |
| System and Technological advancement (STA) | 1/2 | 1/3 | 1/2 | 1 | 0.1258 |

**Table 6.** Comparison of main CSFs of CBML by DM2.

| Main CSFs of CBML | OMR | CLE | CSC | STA | Eigenvalue |
|---|---|---|---|---|---|
| Organizations' Management Readiness (OMR) | 1 | 2 | 3 | 3 | 0.4464 |
| Cloud M-Learning Essentials (CLE) | 1/2 | 1 | 1 | 3 | 0.2373 |
| Cloud Services Compliance (CSC) | 1/3 | 1 | 1 | 3 | 0.2180 |
| System and Technological advancement (STA) | 1/3 | 1/3 | 1/3 | 1 | 0.0983 |

**Table 7.** Comparison of main CSFs of CBML by DM3.

| Main CSFs of CBML | OMR | CLE | CSC | STA | Eigenvalue |
|---|---|---|---|---|---|
| Organizations' Management Readiness (OMR) | 1 | 2 | 3 | 3 | 0.4464 |
| Cloud M-Learning Essentials (CLE) | 1/2 | 1 | 1 | 3 | 0.2373 |
| Cloud Services Compliance (CSC) | 1/3 | 1 | 1 | 3 | 0.2180 |
| System and Technological advancement (STA) | 1/3 | 1/3 | 1/3 | 1 | 0.0983 |

**Table 8.** Synthesized results (DM1 to DM3).

| Main CSFs of CBML | OMR | CLE | CSC | STA | Eigenvalue |
|---|---|---|---|---|---|
| Organizations' Management Readiness (OMR) | 1.00 | 2.00 | 3.00 | 2.29 | 0.4262 |
| Cloud M-Learning Essentials (CLE) | 0.50 | 1.00 | 1.59 | 3.00 | 0.2688 |
| Cloud Services Compliance (CSC) | 0.33 | 0.63 | 1.00 | 2.62 | 0.1919 |
| System and Technological Advancement (STA) | 0.44 | 0.33 | 0.38 | 1.00 | 0.1132 |

**Table 9.** Synthesized weight and rank of CBML main factors and subfactors Using AHP-GDM.

| Main CSFs of CBML | Weight | Subfactors of CBML | Local Weight | Global Weight |
|---|---|---|---|---|
| Organizations' Management Readiness (OMR) | 0.4262 | Service Support (SS) | 0.412 | 0.175 |
| | | Increased Productivity (IP) | 0.281 | 0.120 |
| | | Organizational Culture (OC) | 0.191 | 0.081 |
| | | Commitment toward M-Learning (CTL) | 0.116 | 0.050 |
| Cloud M-Learning Essentials (CLE) | 0.2688 | Collaborative M-Learning Environment (CLE) | 0.297 | 0.080 |
| | | User's Digital Literacy & Attitude (UDA) | 0.231 | 0.062 |
| | | Perceived usefulness (PU) | 0.255 | 0.069 |
| | | Motivation (MO) | 0.130 | 0.035 |
| | | Relative advantage (RA) | 0.088 | 0.024 |
| Cloud Services Compliance (CSC) | 0.1919 | Cloud Services (SaaS, PaaS, IaaS) (CS) | 0.416 | 0.080 |
| | | Service Level Agreement (SLA) | 0.255 | 0.049 |
| | | Data Security and Privacy (DSP) | 0.193 | 0.037 |
| | | Reliability and Availability (RAA) | 0.136 | 0.026 |
| System and Technological Advancement (STA) | 0.1132 | Cloud learning Devices (CLD) | 0.406 | 0.046 |
| | | Technological Compatibility (TC) | 0.316 | 0.036 |
| | | User-friendly Design (UFD) | 0.154 | 0.017 |
| | | Internet Bandwidth (IB) | 0.124 | 0.014 |

FAHP was also used to determine the relative weights of the CBML main criteria and subcriteria. A fuzzy scale employing TFN and reciprocal values of TFN was employed. Table 10 indicates the fuzzy scale based on TFN. When determining the weight of the main factors and subfactors of CBML, the fuzzy scale was utilized. The various steps involved, as discussed in the earlier section, were followed to obtain the weights. Table 11 shows one such pairwise comparison. Table 12 demonstrates CBML's main factors and subfactors composite weights and rankings. It was possible to compare the priority obtained using AHP-GDM and FAHP, as shown in Table 13. The result obtained using the AHP-GDM process for prioritization of CSFS of CBML was compared using FAHP. FAHP ensures accuracy in decision-making while making pairwise comparisons. The vagueness in decision-making was removed using TFN. It also helped to remove biased decision-making. Furthermore, the weights of the main CSFs CBML were presented in Figure 6, whereas Figure 7 demonstrated the local and global weights for CBML subfactors. The local weights were obtained to provide the priority of subcriteria, whereas global weights provided the overall priority of main CSFs of CBML

**Table 10.** TFN Scale.

| Linguistics Scale for Importance | Triangular Fuzzy Scale | Triangular Fuzzy Reciprocal Scale |
|---|---|---|
| Equally Important (EI) | (1, 1, 1) | (1, 1, 1) |
| In-between Value | (1, 2, 3) | (1/3, 1/2, 1/1) |
| Weakly More Important (WMI) | (2, 3, 4) | (1/4, 1/3, 1/2) |
| In-between Value | (3, 4, 5) | (1/5, 1/4, 1/3) |
| Strongly More Important (SMI) | (4, 5, 6) | (1/6, 1/5, 1/4) |
| In-between Value | (5, 6, 7) | (1/7, 1/6, 1/5) |
| Very Strongly More Important (VSMI) | (6, 7, 8) | (1/8, 1/7, 1/6) |
| In-between Value | (7, 8, 9) | (1/9, 1/8, 1/7) |
| Absolutely More Important (AMI) | (9, 9, 9) | (1/9, 1/9, 1/9) |

**Table 11.** Pairwise comparison of the main CSF of CBML using FAHP.

| Main CSFs of CBML | OMR | CLE | CSC | STA | Weights |
|---|---|---|---|---|---|
| Organizations' Management Readiness (OMR) | (1, 1, 1) | (1, 2, 3) | (2, 3, 4) | (1, 2, 3) | 0.3982 |
| Cloud M-Learning Essentials (CLE) | (1/3, 1/2, 1) | (1, 1, 1) | (1, 1, 1) | (2, 3, 4) | 0.2963 |
| Cloud Services Compliance (CSC) | (1/4, 1/3, 1/2) | (1, 1, 1) | (1, 1, 1) | (2, 3, 4) | 0.1922 |
| System and Technological advancement (STA) | (1/3, 1/2, 1/1) | (1/4, 1/3, 1/2) | (1/4, 1/3, 1/2) | (1, 1, 1) | 0.1133 |

**Table 12.** Composite rank and weight of main factors and subfactors of CBML Using FAHP.

| Main CSFs of CBML | Weight | Subfactors of CBML | Local Weight | Global Weight |
|---|---|---|---|---|
| Organizations' Management Readiness (OMR) | 0.4262 | Service Support (SS) | 0.398 | 0.164 |
| | | Increased Productivity (IP) | 0.296 | 0.122 |
| | | Organizational Culture (OC) | 0.192 | 0.079 |
| | | Commitment toward M-Learning (CTL) | 0.113 | 0.047 |
| Cloud M-Learning Essentials (CLE) | 0.2688 | Collaborative M-Learning Environment (CLE) | 0.275 | 0.069 |
| | | User's Digital Literacy & Attitude (UDA) | 0.236 | 0.059 |
| | | Perceived usefulness (PU) | 0.236 | 0.059 |
| | | Motivation (MO) | 0.142 | 0.036 |
| | | Relative advantage (RA) | 0.112 | 0.028 |
| Cloud Services Compliance (CSC) | 0.1919 | Cloud Services (SaaS, PaaS, IaaS) (CS) | 0.419 | 0.092 |
| | | Service Level Agreement (SLA) | 0.256 | 0.056 |
| | | Data Security and Privacy (DSP) | 0.192 | 0.042 |
| | | Reliability and Availability (RAA) | 0.132 | 0.029 |
| System and Technological advancement (STA) | 0.1132 | Cloud learning Devices (CLD) | 0.396 | 0.046 |
| | | Technological Compatibility (TC) | 0.324 | 0.038 |
| | | User-friendly Design (UFD) | 0.151 | 0.018 |
| | | Internet Bandwidth (IB) | 0.129 | 0.015 |

**Table 13.** Comparison of composite weights and ranking of CBML factors And subfactors using AHP-GDM and FAHP.

| Main CSFs of CBML | Main CSFs of CBML Weightage | | Subfactors of CBML | Local Weights of CBML | | Global Weights of CBML | | Overall Ranking | |
|---|---|---|---|---|---|---|---|---|---|
| | AHP-GDM | FAHP | | AHP-GDM | FAHP | AHP-GDM | FAHP | AHP-GDM | FAHP |
| Organizations' Management Readiness (OMR) | 0.426 | 0.412 | Service Support (SS) | 0.412 | 0.398 | 0.175 | 0.164 | 1 | 1 |
| | | | Increased Productivity (IP) | 0.281 | 0.296 | 0.120 | 0.122 | 2 | 2 |
| | | | Organizational Culture (OC) | 0.191 | 0.192 | 0.081 | 0.079 | 3 | 4 |
| | | | Commitment toward M-Learning (CTL) | 0.116 | 0.113 | 0.050 | 0.047 | 8 | 9 |
| Cloud M-Learning Essentials (CLE) | 0.269 | 0.251 | Collaborative M-Learning Environment (CLE) | 0.297 | 0.275 | 0.080 | 0.069 | 5 | 5 |
| | | | User's Digital Literacy & Attitude (UDA) | 0.231 | 0.236 | 0.062 | 0.059 | 7 | 6 |
| | | | Perceived usefulness (PU) | 0.255 | 0.236 | 0.069 | 0.059 | 6 | 7 |
| | | | Motivation (MO) | 0.130 | 0.142 | 0.035 | 0.036 | 13 | 13 |
| | | | Relative advantage (RA) | 0.088 | 0.112 | 0.024 | 0.028 | 15 | 15 |
| Cloud Services Compliance (CSC) | 0.192 | 0.273 | Cloud Services (SaaS, PaaS, IaaS) (CS) | 0.395 | 0.419 | 0.080 | 0.092 | 4 | 3 |
| | | | Service Level Agreement (SLA) | 0.261 | 0.256 | 0.049 | 0.056 | 9 | 8 |
| | | | Data Security and Privacy (DSP) | 0.138 | 0.192 | 0.037 | 0.042 | 11 | 11 |
| | | | Reliability and Availability (RAA) | 0.206 | 0.132 | 0.026 | 0.029 | 14 | 14 |
| System and Technological advancement (STA) | 0.113 | 0.117 | Cloud learning Devices (CLD) | 0.401 | 0.396 | 0.046 | 0.046 | 10 | 10 |
| | | | Technological Compatibility (TC) | 0.307 | 0.324 | 0.036 | 0.038 | 12 | 12 |
| | | | User-friendly Design (UFD) | 0.176 | 0.151 | 0.017 | 0.018 | 16 | 16 |
| | | | Cloud learning Devices (CLD) | 0.115 | 0.129 | 0.014 | 0.015 | 17 | 17 |

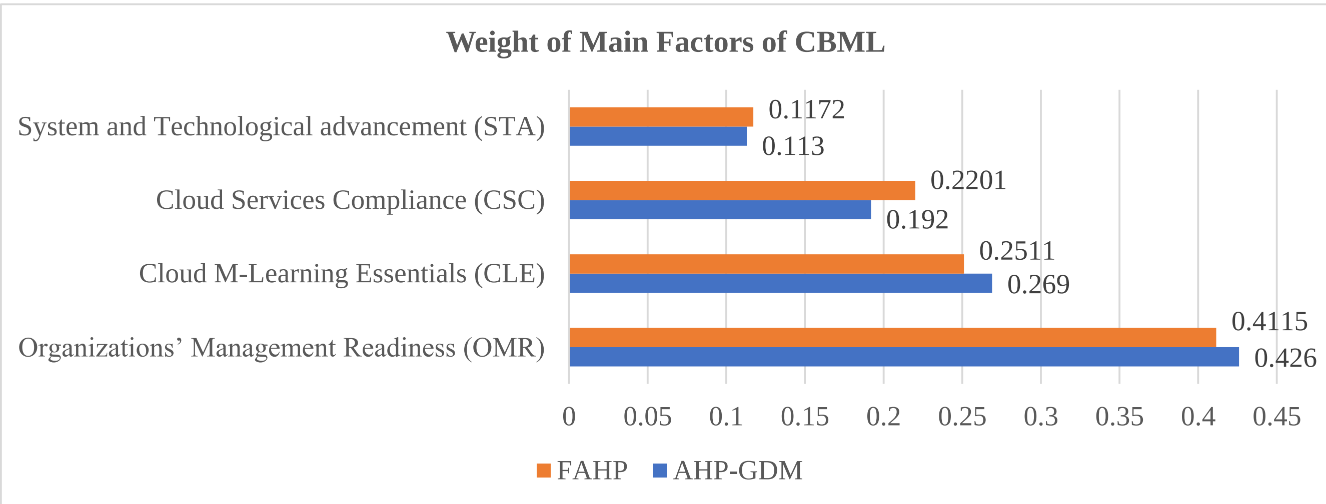


**Figure 6.** Weights of main factors of CBML.

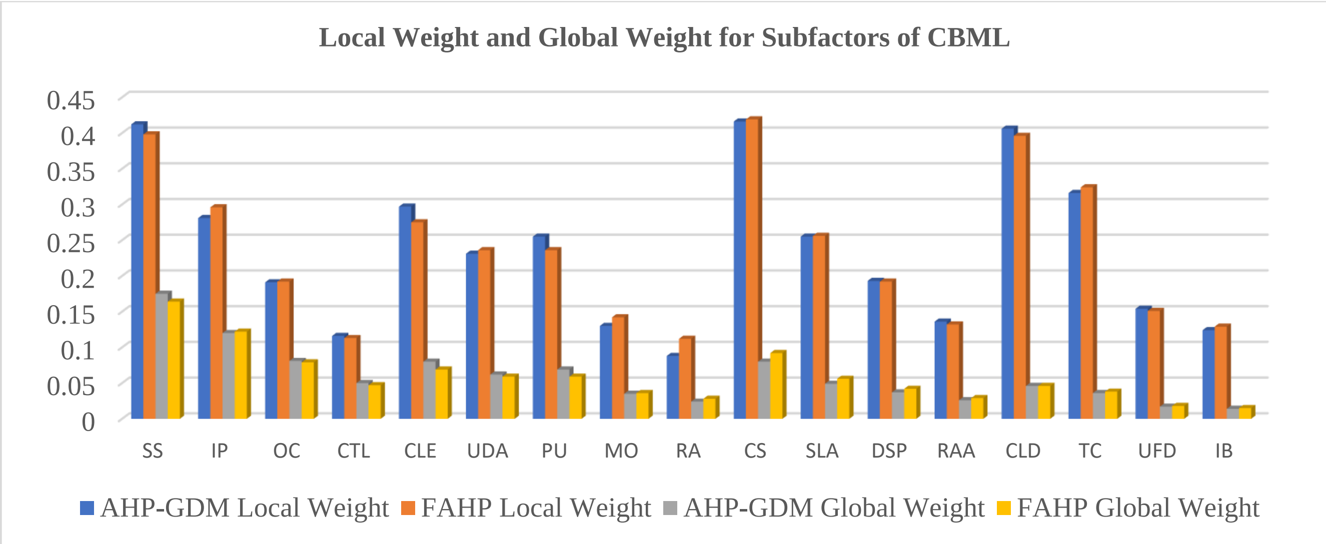


**Figure 7.** Local weight and global weight for subcriteria of CBML.

## 5. Results and Discussions

Apart from M-Learning, CBML also plays a vital role in the teaching–learning system. Smartphones with greater capabilities have made it possible to break the barriers of constrained classroom teaching. The internet revolution has increased the dissemination of knowledge through cloud-based mobile learning. Based on AHP-GDM and FAHP modeling, the weights of various main factors and subfactors of CBML were obtained. The weights obtained for the main CSFs of CBML through AHP-GDM and FAHP modeling were: OMR (0.426) $>$ *CLE* (0.269) $>$ *CSC* (0.192) $>$ *STA* (0.113), whereas for FAHP, the weights obtained were: OMR (0.421) $>$ *CLE* (0.251) $>$ *CSC* (0.273) $>$*STA* (0.117), where $>$ indicates the preference over other as shown in Figure 8.

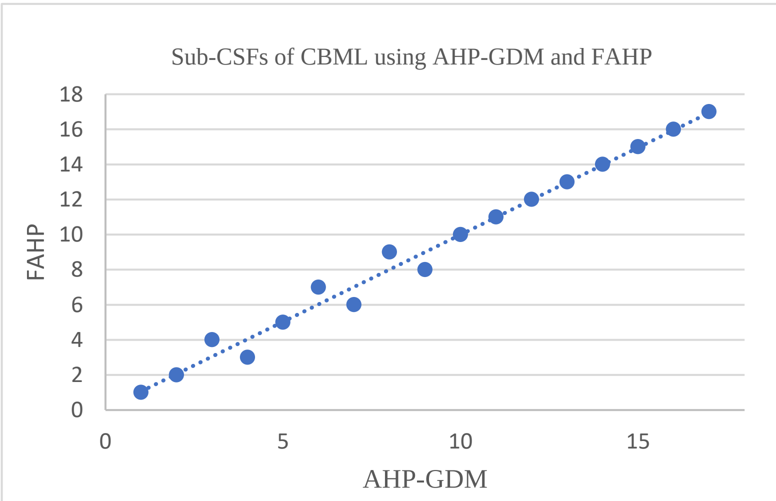


**Figure 8.** The Spearman global rank coefficient for subcriteria of CBML.

Organizations management readiness (OMR) plays a significant role in initiating CBML in the teaching–learning system. Cloud M-Learning Essentials (*CLE*) form the essential component in realizing a CBML system. Cloud services compliance (*CSC*) makes it possible to adhere completely to cloud services for continuity and sustainability. System and technological advancement (*STA*) help in keeping pace with technological changes.

Decision makers for CBML administrative readiness or stakeholders may use the present analysis for understanding CSF and their roles in successful CBML implementations.

The ranking obtained through AHP-GDM and FAHP could enable university authorities to understand the critical role being played by each CSF in successful CBML implementations. Further analysis carried out in the present research direction will also help stakeholders to identify and control strategies for effective usage. The ranks obtained by AHP-GDM and FAHP were compared using the Spearman global rank coefficient, which was obtained as 0.992647. The Spearman global rank coefficient is shown in Figure 7. Values closer to 1 demonstrate a more perfect association between the ranks. The rankings of subcriteria of CBML using AHP-GDM and FAHP were nearly the same, indicating consistency in decision making. Thus, it showed nearly perfect positive connotation of ranks.

## 6. Limitations and Scope for Future Work

The success of CBML is greatly influenced by its main factors and subfactors. A flawless and effective implementation of a CBML system may be accomplished by adhering to the main factors and subfactors of CBML. The main factors and subfactors of CBML's achieved priorities and rankings can be generalized, albeit with some exceptions. The current study used a small number of main factors and subfactors of CBM and a limited number of DMs for AHP-GDM and FAHP. A comprehensive group of main- and sub-CSFs of CBML, together with a broad group of DMs, could be used in future studies to generalize results and meet the expectations of a larger group of higher educational institutes. The weight and rank of the main factors and subfactors of CBML could also be assessed utilizing additional MCDM techniques in a crisp and fuzzy environment. The success of CBML demands a proactive strategic approach for its success; hence, further study could lead to the development of suitable strategies depending upon the CBML SCFs.

## 7. Conclusions

The rapid changes in internet technology and mobile technology could help in achieving sustainable CBML implementation and effective usage in teaching–learning. The teaching–learning process through CBML will enhance the quality of education with an enhanced user-friendly environment and a shift away from face-to-face classroom teaching. Utilizing E-Learning and M-Learning in higher educational institutes is a strategic decision that university managers must consider under different circumstances. Face-to-face teaching–learning was hampered due to the COVID-19 pandemic and universities were compelled to switch to E-learning in many countries. Sustainable M-Learning is one of the available alternatives to E-Learning for enhancing user-friendliness in the teaching–learning process. The selection of E-Learning and M-Learning in future teaching–learning strategies is a crucial decision for higher educational institutes. The present research will help to make such a decision under varying conditions. The evaluation of the main factors and subfactors of sustainable CBML will help in decision-making processes with rapidly changing technological development and its acceptance in teaching–learning methodologies to satisfy all the stakeholders. MCDM offers a simple and organized methodological approach to evaluating various teaching–learning options, such as M-learning and E-learning, to see if they will meet a system's future educational needs. In the future, CBML will help move toward a new, ubiquitous learning paradigm and the pervasive extension of E-Learning technologies, thus necessitating strategic approaches.

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